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Title: The effects of social information on volunteering: a field experiment

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Abstract: Research indicates that providing social information about other people's charitable donations can increase individual contributions. However, the effects of social information on volunteering time are underexplored. In this field experiment we measure the effects of different levels of feedback about other people's time contributions (very high, high and moderate) on individuals' hours of volunteering. The experiment was conducted with students from English universities volunteering for a variety of organizations and with a group of predominantly older people volunteering for a national charity in England. Social information did not increase volunteering for either group relative to a control group receiving individualised feedback with no social comparison. For students whose baseline volunteering time was lower than the median, social information had a demotivating effect, reducing their volunteering, suggesting that donating time is different to donating money.

Introduction

The question of why and under what circumstances individuals make charitable donations has long been of interest across the social sciences. There is now a substantial weight of laboratory evidence demonstrating an effect on individual contributions of a range of social influences such as reciprocity, social norms, trust, and knowledge of other people's contributions (Keser & Van Winden, 2000; Fischbacher et al. 2001; Eckel & Grossman, 2003; Fehr & Gintis, 2007). In recent years there has been a growth in field and online experiments investigating the influence of social information on charitable giving, i.e. information about other people's financial donations, much of which indicates positive effects (List & Lucking-Reiley, 2002; List & Rondeau, 2003; Frey & Meier, 2004; Shang & Croson, 2005; 2009; Heldt, 2005; Karlan & List 2007; Martin & Randall, 2008; Croson & Shang, 2013; Anik et al. 2014).

There is also increasing research interest in the effects of social information on prosocial acts like recycling (Nomura et al. 2011), re-using hotel towels (Goldstein et al. 2008), writing voluntary online film reviews (Yan Chen et al., 2010), and on political acts such as voting (Gerber et al. 2008) and participating in online petitions (Margetts et al. 2013), as well as simple tasks that involve people giving small amounts of time to raise money for charity (Ariely et al., 2009). However, there is currently very little research on the effects of social information on donations of time for more sustained, regular face-to-face volunteering for charitable causes. This research seeks to fill this gap.

Given the support for social information effects on charitable donations and other prosocial acts, there is great potential in reading across these theories to analogous effects on volunteering, which like charitable donations, is a non-remunerated activity that benefits other people and society more widely. While some studies have explored the influence of

factors in the social environment on volunteering, for example studies on motivation and incentives (Carpenter and Myers 2010), tailored feedback (Al-Ubaydli and Lee 2011) and the presence/ absence of authority figures and excuses (Linardi and McConnell, 2011), few studies on volunteering have explored the effects of social information. Furthermore, social information has practical importance as a possible mechanism which can be manipulated by policymakers or practitioners to boost volunteering levels.

In this paper we present field experiments which vary the nature of social information provided to volunteers. We investigate the effects on volunteering rates of providing feedback about an individual's contribution in comparison to the median of the top 10% of contributors (hereafter 'very high'), the median of the top 20% (hereafter 'high') and the median contribution overall (hereafter 'moderate'). Evidence from field experiments is important for evaluating theory in real volunteering contexts, and potentially informing organisations' policies to encourage donation of time; indeed there have been calls for field experiments exploring this topic (Mason, 2013). Field experiments have the advantage of allowing causal inference to be made, having high internal validity (Gerber & Green, 2012). They also can provide high external validity as compared to laboratory studies because they occur in real world settings, albeit with findings that are specific to the context in which they are generated.

Section one outlines the theory of social information in relation to financial donation, how it can be read across to volunteering time, and sets out our hypotheses derived from the theory of social information. Section two explains the design of the field experiments. Section three presents the findings which challenge the theory of social information effects on volunteering. Section four discusses the study implications.

I Social comparison and the role of social information in volunteering

Field experiments exploring the effects of social information demonstrate that providing people with information about the financial charitable contributions of others increases their propensity to donate (Heldt, 2005; Martin and Randall, 2008; Soetevent, 2005). Yet there are mixed findings on the quantity or scale of giving which has greatest influence when presented as social information. Field experiments have manipulated different ‘levels’ of social information to compare the effect of information about extreme, high, medium and low level contributions of other people. Some studies provide participants with social information on the proportion of other people donating (Frey & Meier, 2004; Anik et al. 2014), while others provide information on the amount contributed by people in certain percentiles within a scale of donations (Shang & Croson, 2009; Croson & Shang, 2013), or the proportion of seed money already raised towards a target (List & Lucking Reiley, 2002). These studies overall indicate that social information within the range of 64-95% of the particular scale in question (i.e. approximately the top third to the top 5% of donors or donation levels), are the most effective levels of social information. Experiments that incorporate tests of social information levels that are *extremely* high, i.e. social information about contributions of those in the 99th percentile (Croson & Shang, 2013), or information which states that 100% of other people donate (Anik et al. 2014), indicate that these more extreme levels are ineffective, suggesting boundary effects of social information.

The effects of social information are likely to be contingent on a person’s own existing contribution level in relation to the information presented. For instance, Yan Chen et al. (2010) in their study of voluntary online film reviewing, find that providing social information about the number of movie ratings of the median user led to a five-fold increase in reviewing levels of those who were already below the median, but *decreased* the monthly

number of film ratings amongst study participants who were already above the median, by 62% (see also Nomura et al. 2011; Frey and Meier, 2004). Such effects of higher than average contributors decreasing their participation in response to receiving information about averages is known as the ‘boomerang effect’ (Schulz et al. 2007).

Research on social information is rooted in social comparison theory originally associated with Festinger (1954) and subsequently refined in the social psychology literature (Taylor, Buunk and Aspinwall 1990; Wills and Suls 1991; Gibbons and Buunk 1999; Suls et al. 2002). The theory suggests that people have a tendency to make comparisons with others when evaluating their own opinions and abilities, particularly when there are no objective standards against which to judge themselves, or in situations of uncertainty. Social comparison theory further suggests that comparison is more likely with those we perceive as similar to ourselves. Drawing on this theory we suggest that social information is influential in relation to charitable giving and other prosocial behaviours because it provides a benchmark or social cue about the appropriate level. The theory also suggests that social information will be most influential if it is made clear that the information derives from an individual’s peer group.

Applying the theory of social information to volunteering, we suggest that social information about others’ contributions, particularly high or very high contributions, will enhance individual contributions. We expect social comparison to be influential in this context for two reasons.

First, in situations of norm ambiguity people are more likely to be influenced by social information and to look to others for cues (Shang & Croson, 2009; Yan Chen et al. 2010). We argue that volunteering fits into this category: how much time to give to volunteering is relatively ambiguous, especially when compared to paid work where there is a typical weekly time contribution, governed by working time regulations or employment

contracts. In the absence of clear social norms or an objective standard for levels of voluntary commitment, social information may provide an implicit signal about a norm. Our experiment provides participants with feedback about other people's contributions relative to their own, thus providing a signal about a social norm and allowing them to act on this information by adjusting their positions. Research has demonstrated that people tend to underestimate the prosocial behaviour of their peers (Frey & Meier, 2004) and use these low estimates as a standard against which to judge themselves (Schultz et al. 2007). Hence, providing feedback about others' contributions may drive up individual contributions by letting people know that their peers' contributions are higher than previously thought.

Second, comparison takes place within groups who may perceive themselves as likeminded or similar, something which the theory of social comparison suggests should enhance the effect of social information. Peer group influences and expectations have been shown to be a particularly important driver for volunteering (Lee et al. 1999). With regards student volunteering, a social norm of volunteering by key reference groups of parents, siblings and close friends is associated with higher levels of volunteering (Francis 2011). We attempt to construct groups that are similar to one another, either because of belonging to a single organisation (the national charity) and therefore possibly sharing similar values or aims, or by virtue of being students at a similar life-stage sharing similar experiences. The individuals do not know one another personally, so our groups are not true peers of personal contacts, nonetheless the groups we construct provide a good proxy for this, and are therefore possibly susceptible to the effects of social information.

A necessary condition for reading across such theories of social information is that individuals volunteering have the same ability to make adjustments to their volunteering time as participants in the charitable giving experiments have with their financial donations. As we discuss further below, this is a condition met in our experimental contexts.

Our hypotheses were that social information about high and very high levels of volunteering of others would both increase time given to volunteering, with information about the top 20% being even more motivating than information about the top 10%, with the latter perhaps seeming less attainable. We purposefully chose to investigate the effect of high and very high levels of time donation as opposed to extremely high levels (e.g. top 1%) because of the existing finding that extremes can be off-putting and de-motivating (Croson & Shang, 2013; Anik et al. 2014). Following Yan Chen et al. (2010), we hypothesised that moderate, i.e. median levels of volunteering, would be motivating but only for those with baseline (T1) scores below this level, while it would be de-motivating for those with above median baseline volunteering, the so-called ‘boomerang effect’ (Schultz et al. 2007). As an extension of this, we wanted to test the effect of *all* the social information treatments contingent on a person’s baseline contributions. We hypothesised that all social information treatments would be more effective for those with below median scores than those with above median scores.

II Research method

Setting and participants

The field experiments were conducted in England on two populations: a group of students from across five UK universities and a group of predominantly older and retired people. We focus on these groups because both students and older people constitute an important source of volunteer labour (Handy et al. 2010; Davis Smith and Gray, 2005).

The study was conducted as two separate sessions of the same experimental design. Care was taken to ensure that the experiment’s implementation was as similar as possible in both sessions. The wording and implementation of the treatments in each of the sessions was identical. The first session, with the students, took place from January-March 2014, and was

chosen to avoid the main exam period which might have adversely affected participation in the study and in volunteering. The second session, with the older group of volunteers, was conducted from August-October 2014. Sample characteristics are described in Table 1.

Participants were involved in a diverse range of volunteering activities, and had considerable freedom to increase or decrease their hours during the study. The student volunteers were typically involved in befriending, leading groups, and organising events and in services for elderly or homeless people. The older group of volunteers were all volunteering for the same national charity whose role is to protect and maintain historic properties; they conducted a range of activities associated with the upkeep and operation of these properties, including stewarding, buildings maintenance and visitor transportation. Most of the older volunteers also engaged in additional volunteering outside of the national charity, such as community transport provision, volunteering in schools and churches, and committee participation. The volunteering data reported for the group of older volunteers relates to their volunteering for the national charity as well as these other causes.

Recruitment and sample size

We targeted the advertising for the study at those who were already volunteering or were planning to volunteer during the time of the study, and used a variety of methods to recruit participants. With the assistance of the university volunteering units and the national charity, we sent invitation emails via distribution lists, and placed adverts on their websites, Facebook sites, E-newsletters and notice boards. We used similar text in each format, slightly tailored to reflect the media of the advertisement and target group¹.

We offered a prize draw for Amazon vouchers to provide an incentive to participate in the study. In considering whether to include an incentive, we weighed the potential crowding out effects this could produce on people's volunteering levels against the positive inducement

of a prize draw. We chose to include the prize draw on the basis that the prizes were linked to participating in the study not to actual volunteering levels, and that it is fairly standard to offer a small incentive to motivate participation in a research study. We made it possible for people to opt out of the prize draw although none did.

The study had two stages (see Figure 1). Our final sample on which we conduct our data analysis consists of those who stayed in the study throughout both stages. We aimed for a sample size sufficient to detect effect sizes found in previous studies testing the effects of social information on charitable donations and other prosocial behaviours, of around 300 (Yan Chen et al. 2010; Croson and Shang, 2013). In this area there is limited previous research so the size of expected effects is less certain than for topic areas where findings are more established. However, in particular, we drew on the research of Yan Chen et al. (2010). They found a strong effect of social information on voluntary activity (530% increase for below median participants) based on a sample size of 398. We also drew on Linardi and McConnell (2011) who allocated 156 subjects to three experimental groups in a laboratory experiment on the closely related topic of natural volunteering behaviour. Our overall sample size combining both sessions of the experiment was 284 (157 in the first session; 127 in the second). As shown in our results section, we use pre-test and post-test data, and difference in differences analysis which allows us to economise on the sample size. The difference in difference approach is preferable to a design relying only on comparisons of ex post outcome measures where the substantial baseline variation in hours volunteered is not taken into account.

Procedure

We used a standardised procedure for both sessions of the experiment (see Figure 1 for a flowchart of the experimental design and procedure)². Participants registered for the study on

a bespoke study website called ‘Your Time Counts’. Registration involved completing a short survey providing us with baseline information (see table 1) about the person’s current volunteering, and a data on a variety of variables that research indicates are correlated with volunteering, including education, age, gender, employment status, number of hours in paid employment, a past history of volunteering, and length of time volunteered in an organisation (Lee et al. 1999; Penner & Finklestein, 1998; Grube & Pilavian, 2000; Wilson, 2012). In the survey we explicitly defined volunteering as “...unpaid help you give to benefit others or the environment. This help can be as part of a group, club or organisation, or direct to an individual who is not a relative. Taking part in a sponsored event, though very valuable in itself, is treated as a different type of activity, hence not included in our definition of volunteering.”

We emailed participants asking them to make a note of their hours volunteered and the type of volunteering undertaken, for the forthcoming four-week period. A reminder was sent half way through this period, and another email sent at the end of the four weeks asking participants to log their volunteering activity on the Your Time Counts website. The website was open for recording for a week, with reminders sent half way through the week and again near the end of the week. Feedback was then generated corresponding to our treatment groups (see section below) and sent to participants, with participants randomly assigned in equal numbers to receive one of three forms of treatment or a control treatment.

In the same email that contained the feedback, participants were asked to record their volunteering for a second four-week period. The same procedure was used again in this period, in terms of reminders and recording data. After logging their data for the second time period, participants were sent a final summary showing their time contribution. We believed a four-week period for each phase of the study was appropriate as this provided sufficient

time for people to adjust their volunteering hours in response to social information feedback, but was also condensed enough to maximise ongoing participation until the end of the study.

[Figure 1 here]

Figure 1 indicates the level of attrition in the study between the first and second four-week periods. We performed checks to test whether post randomization attrition between period 1 and period 2 was correlated with treatment group, and found this not to be the case³. We also compared time 1 volunteering hours for those who dropped out of the experiments after receiving the social information and those who completed the study. We found that those dropping out had lower mean volunteering scores at time 1, both for the student sample and the sample of older volunteers, suggesting that the social information may have been off-putting for those doing less volunteering after time 1⁴. This also suggests that those in our final sample are those with higher baseline (time 1) volunteering levels.

Randomisation

Simple randomisation was used for both sessions of the study, with an approximately even number of participants randomly allocated to each treatment group (see figure 1). Sequence generation was by computerised random number generator. In the student session the randomisation was first stratified by institution using a block size of 4 to ensure students from different universities were allocated in equal numbers to the different treatment conditions. The participants were then allocated to one of four trial arms. The randomisation process for the student experiment was conducted by a statistician from an outside research institution, and for the national charity experiment, by a research fellow based at the employing university of one of the co-authors - both of whom were independent of the

research team. To assess the success of the randomisation process we performed balance checks testing for differences on key covariates between each treatment group and all other treatment groups, using probit regression (see table 1 for descriptive statistics). The regression analysis revealed that the groups were evenly balanced across groups apart from on the age covariate, consistent with chance imbalance we would expect with the randomisation process.

Treatments

The first group received information about their own time contribution, in hours, compared to the median time contribution, in hours, of all participants (moderate social information). The median contribution sends an implicit signal about a social norm for time contributions. The second group received information about their own time contribution compared to the median of the top 10% of participants (very high social information), while the third group received information about their own time contribution compared to the median of the top 20% of participants (high social information). In each of the treatments, the term ‘average’, a more familiar term, was used on the bar graph feedback, and in a footnote it was explained that the average referred to the median, with a definition of median provided. Medians were used rather than means to avoid extreme responses skewing the levels of time presented for each of the groups. A fourth group received feedback about their own time contribution but with no social comparison. This group is our control group which we compare with each treatment group in our analysis.

The feedback was provided in a simple bar graph showing an individual’s own time contribution in hours, either on its own for the control group, or adjacent to the relevant median in hours for each of the treatment groups, using real data from the sample (see Appendix 1 for a sample of the feedback sent to an individual in the top 10% treatment

group). A bar graph was used alongside the numerical figures because research indicates that people are influenced by visual information cues containing relative scores and that presentation format is critical in determining the weight people give to information, with simplicity in visual format generating greater receptiveness (Hibbard et al. 2002; James & Moseley, 2014). The text accompanying the graph (depending on treatment group) stated: ‘Here is how your time contribution compares to average (median) time contribution of **participants/ the top 10% of participants/ the top 20%** in this study, over the past four weeks’. The relevant comparison was emboldened to draw attention to the social information treatment itself. The control statement simply read ‘here is your time contribution over the past four weeks’, with a single bar graph and no comparison.

Outcome measures

Our outcome measure was the number of hours volunteered over a four-week period. Information about hours volunteered was provided by the respondents themselves via the study website. Because the study relied on self-report data we took steps to minimise the likelihood of false reporting or over-reporting; participants were asked to provide details of the nature of their activity from a drop-down list and asked to name any relevant organisations for which they had volunteered. We also said that we planned to contact a sample of the named organisations to find out more about the volunteering options they offered and to involve them further in the study, creating an impression that misrepresentation by participants might be discovered by this auditing. As a reliability check, following the last four-week period of the student study, we approached a sample of the organisations cited and asked whether they had had students volunteering with them in the past four weeks, without asking for individual names because of data protection law. The majority that we contacted responded, with all respondents confirming the presence of

student volunteers during the relevant time period.

Analysis

Our analytical approach was to use a baseline measure before randomisation (time 1) and compare differences between groups between time 1 ('pre-test') and time 2 ('post-test'). Many field experiments simply use randomisation of treatment allocation followed by a measure of the outcome. There is considerable variability introduced by this approach because participants vary so much on characteristics affecting outcomes and, by chance, these can show up in imbalance on outcomes post randomisation that are not caused by treatment. In this way, much of the variation between individuals that has consequence for their volunteering behaviour is captured in the baseline measure and is removed in the before and after difference measure.

III Results

Table 1 provides baseline data on each of our treatment groups and overall, collected from the survey conducted at the outset of the experiment. The table provides information about characteristics of the sample to which the results pertain, and a balance check on treatment versus control groups.

[Table 1 here]

Summary statistics for our student sample and our national charity sample are provided in Table 2, specifically mean hours volunteered for each treatment group at time 1 (i.e. pre-intervention after the first four-week recording period) and at time 2 (i.e. post intervention, after the second four-week recording period). To reflect our analytical modelling strategy, we

provide data for each sample overall, and then separately for those with below median scores at time 1 and those with scores greater than or equal to the median at time 1. The data refer only to those who stayed in the study until the end.

[Table 2 here]

Tables 3 and 4 provide estimates of the effect of each of our treatments relative to the control group, using linear regression models, for our student group and our group of national charity volunteers respectively. Our models take the difference between time 2 and time 1 scores as our dependent variable, with the three treatment groups as our independent variables, and the control group as the baseline reference group (constant). As discussed above, we hypothesised that the social information would have different effects depending on people's baseline participation rates, in our case their level of volunteering during the first four weeks of the study. Following the approach of Yan Chen et al. (2010), we compare those with time 1 scores below the median score of all participants, those with time 1 scores greater than or equal to the median score of all participants, and all participants together. Each table contains three models to reflect this.

From Table 3 (model 1) we see that for students overall, the social information treatments have no effect that can be detected as significantly different from zero relative to the control. However, those students who volunteer fewer hours than the overall median participant at time 1 are significantly affected by the treatments (model 2); specifically, and contrary to expectations, we see a strong *demotivating* effect of all the social information treatments for this group. Expressed in descriptive statistics, the change in hours for the control group between time 1 and time 2 was an increase of 3.57 hours, compared to an increase in just 0.17 hours for the median group, an increase of 0.65 hours for the top 10% group and a reduction of 0.24 hours for the top 20% group. This finding suggests that those

who are given information that they are below the median in terms of hours contributed may feel the level of volunteering of others is unattainable or that they do not need to try when others are doing more. For the control group who receive individual feedback with no social comparison, there is a significant rise in hours from time 1 to time 2. This indicates that a simple reminder about the hours they had done may have been enough to motivate these people to do more. This interpretation seems plausible: practitioners consulted during the dissemination phase of the study suggested that being reminded of the contribution or difference they had made might be enough to motivate people to do more.

Model 3 shows that those with above average hours at time 1 slightly increase their hours at time 2 upon receiving social information relative to the control group in the overall median and top ten percent groups, but the magnitude of the effect is not significant. In summary, we can conclude that social information does not motivate our group of students to volunteer more; in fact, for those whose volunteering is within the lower half of the range, social information has a negative effect, reducing their volunteering levels for all levels of social information provided.

[Table 3 here]

Table 4 indicates that social information has little effect on the group of comparatively older, national charity volunteers. Model 1 shows that for this group as a whole, there is no significant effect of the treatments that can be distinguished as statistically significant from zero. The reduction in hours between time 1 and time 2 is greater for the top 20% group and median treatment group relative the control group but not significantly, and there is virtually no difference between the top 10% treatment group and the control group. There is no clear pattern differentiating the effects of the treatments on those with baseline

volunteering levels below the median (model 2) and above the median (model 3) and no significant effects of the treatments on either of these subgroups.

Overall, this group of volunteers appears not to respond to the effect of social information, perhaps by virtue of their age making them less easily influenced by social information about their peers. The national charity volunteers had volunteered in the charity more than twice as long as the students had been in their universities (mean of 2.22 years vs 4.98 years). It is possible that the volunteering habits of the national charity volunteers are therefore more entrenched than students who are more likely to move in and out of different volunteering roles for shorter time periods. It is also plausible that because these older volunteers did significantly more volunteering hours to begin with, they had less capacity to respond to any incentive aimed at increasing their amount of volunteering.

[Table 4 here]

IV Conclusion

Although social information may positively influence financial donations to charitable causes (Frey & Meyer, 2004; Heldt, 2005; Soetevent, 2005; Martin & Randal, 2008; Shang & Croson, 2009), our research suggests that it has no beneficial effect on donations of time for such causes. While previous research has suggested that it is only extremely high social information (e.g. relating to the equivalent of the top 1% of contributors) which de-motivates people (Croson & Shang, 2013), we find that for volunteers with below median volunteering levels, any level of social information can be de-motivating (moderate, high or very high). The specific levels of social information found to be effective for enhancing contributions in other settings, i.e. information about the contributions of the top third to top 90% of

participants (List and Lucking-Reiley, 2002; Frey and Meier, 2004; Shang and Croson, 2009; Anik et al. 2014), are not effective in the context we studied.

Simply put, our findings are consistent with the reasoning that time is not money, and that people value these two resources differently (Lee et al. 1999; Okada & Hoch, 2004; Ellingson & Johannesson, 2009). Using social information to influence a sustained behaviour like volunteering which requires a significant expenditure of personal time and effort including face-to-face interaction (Lee et al. 1999) is more challenging than seeking to influence one-off acts like financial donation (Linardi and McConnell, 2011). Previous work suggests that a complex array of factors motivates people's volunteering, with some factors being tied to role identity as well as the perceived expectations of others and image motivation (Ariely et al. 2009; Grube and Piliavin, 2000; Carpenter and Myers, 2010). Thus volunteering is a more involved activity than giving money, and consequently a simple numerical benchmark about how much other people do, even if it does send out an implicit social norm, may not be enough in itself enough to encourage people to do more. This null finding is important because it challenges the expectations of the theory of social information as developed in the context of charitable donations.

We were particularly interested in the effect of social information on people with different baseline volunteering levels. Unlike Yan Chen et al. (2010) who find that social information has a large motivating effect for those below the median score, we find that students whose time 1 score for volunteering is below the median are significantly demotivated by receiving social information. The difference in our findings may be due to variety in the voluntary activity being undertaken. In Yan Chen et al.'s study, users of an online system are asked to rate movies, something which could be achieved with a few clicks of a mouse in a matter of minutes. Social information seems to have been an appropriate technique for encouraging this sort of activity, as it appears to be for donating money. Our

outcome measure was hours of volunteering time, usually involving physical effort and interaction with others. This is a more involved and sustained activity and may require a different sort of approach.

Our findings are significant given the growing evidence showing a largely positive effect of social information on charitable giving of money. The implication is that organisations seeking to increase volunteering time should not assume that techniques deployed to increase charitable giving will work in the different context of volunteering. Maintaining an ongoing time commitment from a volunteer labour force is a major challenge facing non-profit organisations, and this study provides an indication of one method that may not be effective in helping attain this.

We conducted the same field experiment on two very different populations; a group of relatively young university students, and a group of older, predominantly retired people. These are both non-waged groups who are important contributors to volunteering efforts, so the findings have relevance for organisations relying on these groups. A limitation of field experiments is that their results are most applicable to the setting in which they are conducted and the particular population studied. Our study took place in England with people who were already volunteering, and those in the final sample had higher volunteering levels than those who dropped out, suggesting that the group of volunteers in our study may have been high-contributing volunteers. While the findings are likely to be relevant both to such groups and to volunteers more generally, replications of the experiments in other settings and with other groups with different baseline volunteering levels would be valuable. In addition, our findings on the subgroup analysis of below and above median participants, we would suggest, are indicative only because of the relatively small groups involved, and replications would therefore be useful with larger samples.

While the social information we tested did not lead to increased volunteering, it is possible that other forms or levels of social information could have positive effects. Our experiment examined the effects of information about the hours volunteered by other people, reporting on the levels of moderate, high and very high contributors. An alternative approach could be to provide feedback on low contributors such as the bottom 10% or 20%, which might motivate people more by invoking positive feelings about their own contribution (although it could also create a boomerang effect and reduce volunteering). Social information could also be used in contexts where the peer groups are more genuine. We used a proxy for peer groups but it is possible that if the individuals in the peer groups are actually known to the participants, social information could have different effects. Our study, like the majority of those on charitable donations, provides numerical feedback, in our case about the number of hours donated. Social information could also be given about the outcomes of the contributions of other people, or in different formats such as vignettes or video footage. Further research should also assess the effect of feedback which reinforces a person's social identity-based motivations for volunteering, for example because of belonging to a group that volunteers. Given that other people's expectations are another important driver of volunteering (Grube and Piliavin, 2000), another line of inquiry (see Cotterill et al. 2013) would be to combine feedback about individual volunteering with publicity or the promise of publicity about contributions.

Appendix 1: Social Information Treatment (Top 10% Treatment Group)

[Manage Profile](#)
[Settings](#)

Dashboard

Record Activity

Activity Statistics

Anne Scutt

Thank you for recording your activity between 04/08/2014 and 31/08/2014.

[Click here to view statistics](#)

Activity Statistics

Statistics for activity between 04/08/2014 and 31/08/2014

Here is how your time contribution compares to the average (median) of the **top 10% of participants** in this study, over the past 4 weeks*

Hours Recorded Comparison

Category	Hours Recorded
Hours recorded yourself	40
Average hours recorded by top 10%	80

*This figure compares your own number of hours volunteered over the past 4 weeks to the median of the 10% of participants in the study who did most volunteering over the same time period (the median is the middle value in a list of numbers ordered from the lowest to the highest).

Statistics Summary

Statistics for activity recorded between 31/08/2014 and 09/09/2014.

185 participants in the volunteering study

40 hours were recorded by yourself

80 average hours recorded by top 10% of participants

WIN

Win vouchers for Amazon
Those completing the study until the end will be entered into our Amazon prize draw.
[Find out more](#)

Most Popular Frequently Asked Questions

Why volunteer?

What's the definition of volunteering?

What is Your Time Counts?

Who are you?

How do I contact the team?

How do I volunteer? Where can I go to do more or different volunteering activities?

Why should I keep a record of my volunteering activity?

How do I register my time?

What happens at the end of the study?

What happens with my information?

Website Navigation

Volunteering Information

Volunteering Links

Selection of Frequently Asked Questions (FAQs)

Get in touch with the team

Privacy Policy and Legal Statement

End notes

¹ Abbreviated version of the invitation email text: ‘The study is called Your Time Counts and investigates why people volunteer and the sorts of things that influence the amount of time people give... the study is only for people who already volunteer or about to start volunteering within the next couple of weeks... It is all done online and should not take up much of your time.... As a thank you, everyone completing the study will be entered into a prize draw to win one of 5 Amazon vouchers, each worth £50, unless you choose to opt out..... Registration for the study is now open. Please click on the link to register’.

² We obtained ethical approval from the participating universities.

³ We performed logistic regressions with each of our sample groups, which indicated no significant effect of treatment group on attrition. The relevant tables can be obtained from the corresponding author.

⁴ Student sample - mean time 1 volunteering score of 11.75 hrs for those who completed versus 6.56 for those that dropped out. National charity volunteers - mean time 1 volunteering score of 33.65 hrs for those who completed compared to 26.92 for those that dropped out.

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Table 1 Baseline Characteristics of Sample#

	Median Treatment %/ (N)	Top 10% treatment %/ (N)	Top 20% treatment %/ (N)	Control Group %/ (N)	All %/ (N)
<i>Student sample</i>					
Mean hrs in paid employment	4.74 (50)	9.24* (46)	3.65 (43)	2.64 (45)	5.10 (184)
Mean Age	26.10 (52)	23.33 (46)	22.81 (43)	25.52 (46)	24.52 (187)
Mean hrs volunteered during previous 4 weeks	9.57 (51)	11.57 (46)	10.45 (43)	10.63 (46)	10.53 (186)
Mean years in organisation	2.13 (40)	2.06 (36)	2.07 (41)	2.62 (34)	2.21 (151)
Already volunteered this year (%)	62 (32)	63 (29)	66 (29)	70 (32)	65 (122)
Gender (% female)	60 (32)	77 (37)	73 (35)	70 (32)	70 (136)
Full time student (%)	94 (49)	94 (43)	100 (44)	91 (42)	95 (178)
Undergraduate (%)	65 (26)	61 (22)	83* (34)	63 (22)	68 (104)
<i>National charity sample</i>					
Mean hrs in paid employment	1.49 (35)	2.91 (35)	1.66 (35)	4.46 (35)	2.63 (140)
Age	63.66 (35)	62.14 (35)	65.54* (35)	61.74 (35)	63.27 (140)
Hours volunteered during previous 4 weeks	25.46 (35)	30.54 (35)	27.94 (35)	27.79 (34)	27.94 (139)
Years in organisation	4.57 (35)	4.86 (35)	5.03 (35)	5.46 (35)	4.98 (140)
Already volunteered this year (%)	100 (35)	100 (35)	97 (34)	100.00 (35)	99 (139)
Gender (% female)	54 (19)	60 (21)	63 (22)	54 (19)	58 (81)
Retired (%)	80 (28)	71 (25)	83 (29)	71 (25)	76 (107)
Possessed degree/ postgrad degree (%)	60 (21)	60 (21)	51 (18)	46 (16)	54 (76)

#Percentages are rounded to nearest %. All other figs are rounded to 2 d.p.

*** p<0.001, ** p<0.01, * p<0.05 (stars indicate statistically significant difference between treatment group & all other groups, using paired sample t-tests for continuous variables & chi squares for categorical variables)

Table 2 Mean hours at t1 and t2 for treatment and control groups

Treatment group	Mean hrs t1 (s.d.)	Mean hrs t2 (s.d.)	Obs	Difference t2-t1
<i>Students - t1 scores < median</i>				
Median	0.44 (1.08)	0.61 (1.85)	23	0.17
Top 10%	0.75 (1.41)	1.40 (2.46)	20	0.65
Top 20%	1.71 (1.86)	1.47 (2.43)	17	-0.24
Control	1.07 (1.07)	4.64 (5.02)	14	3.57*
All groups	0.93 (1.53)	1.78 (3.23)	74	0.85*
<i>Students - t1 scores ≥ median</i>				
Median	20.50 (13.01)	19.09 (13.71)	22	-1.41
Top 10%	21.56 (15.96)	21.13 (18.57)	16	-0.44
Top 20%	20.46 (19.92)	15.08 (9.07)	24	-5.38
Control	23.24 (20.21)	19.48 (18.37)	21	-3.76
All groups	21.39 (17.38)	18.42 (14.89)	83	-2.96
<i>All student volunteers</i>				
Median	10.24 (13.57)	9.64 (13.37)	45	-0.60
Top 10%	10.00 (14.84)	10.17 (15.82)	36	0.17
Top 20%	12.68 (17.80)	9.44 (9.79)	41	-3.24
Control	14.37 (19.05)	13.54 (16.12)	35	-0.82
All groups	11.75 (16.27)	10.58 (13.82)	157	-1.17
<i>National Charity - t1 scores < median</i>				
Median	16.83 (5.95)	17.417 (8.87)	12	0.58
Top 10%	18.18 (5.59)	20.471 (9.34)	17	2.29
Top 20%	19.46 (8.28)	16.637 (14.99)	11	-2.82
Control	15.75 (7.14)	15.700 (9.00)	20	-0.05
All groups	17.33 (6.71)	17.567 (10.31)	60	0.23
<i>National Charity - t1 scores ≥ the median</i>				
Median	44.500 (15.28)	34.546 (24.77)	22	-9.96
Top 10%	52.429 (21.00)	43.429 (30.16)	14	-9.00
Top 20%	52.790 (20.66)	45.316 (24.10)	19	-7.47
Control	43.083 (15.31)	39.250 (21.57)	12	-3.83
All groups	48.254 (18.32)	40.299 (25.12)	67	-7.96**
<i>All national charity volunteers</i>				
Median	34.735 (18.45)	28.500 (22.04)	34	-6.24
Top 10%	33.645 (22.54)	30.8839 (23.99)	31	-2.81
Top 20%	40.567 (23.57)	34.800 (25.21)	30	-5.77

Control	26.000 (17.18)	24.531 (18.68)	32	-1.47
All groups	33.646 (20.91)	29.559 (22.58)	127	-4.09*

*** p<0.001, ** p<0.01, * p<0.05 (stars indicate a statistically significant difference between t1 and t2 using paired sample t-tests)

Table 3 Linear regression showing treatment effects measured in mean hours difference between t2 and t1 (students)

VARIABLES	(1) AllStudents hoursdiff	(2) BelowMedian hoursdiff	(3) AboveMedian hoursdiff
Mediangroup	0.229 (2.852)	-3.398*** (0.933)	2.353 (5.229)
Toptengroup	0.995 (3.004)	-2.921** (0.959)	3.324 (5.688)
Toptwentygroup	-2.415 (2.912)	-3.807*** (0.993)	-1.613 (5.122)
Constant	-0.829 (2.139)	3.571*** (0.736)	-3.762 (3.740)
Observations	157	74	83
R-squared	0.010	0.203	0.013

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table 4 Linear regression showing treatment effects measured in mean hours difference between t2 and t1 (national charity)

VARIABLES	(1) AllNationalcharity Hoursdiff	(2) BelowMedian hoursdiff	(3) AboveMedian hoursdiff
mediangroup	-4.767 (4.525)	0.633 (3.656)	-6.121 (8.314)
toptengroup	-1.338 (4.630)	2.344 (3.303)	-5.167 (9.113)
toptwentygroup	-4.298 (4.669)	-2.768 (3.758)	-3.640 (8.542)
Constant	-1.469 (3.248)	-0.0500 (2.239)	-3.833 (6.687)
Observations	127	60	67
R-squared	0.012	0.031	0.009

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Figure 1 Experimental design and procedure

